Lending Standards, Granular Banks and Aggregate Fluctuations*

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Abstract

This paper develops a quarterly indicator for bank credit supply shocks in Chile from 2009 to 2023. We aggregate changes in lending standards, adjusted for shifts in demand and unobservable factors, exploiting the granularity of banks in the cross-section. Our indicator reflects both idiosyncratic changes in the supply of credit and a common component not driven by demand. We show that a contractionary shock of one standard deviation in our indicator lowers aggregate credit by 0.5% two years following the shock and significantly affects prices and monetary policy. We also highlight the importance of alternative credit sources for the corporate sector to understand the overall implications of contractions in banking credit.

JEL Codes: C32, E32, E44, E51, G21

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1 Introduction

Bank credit is the largest source of finance for households and businesses, accounting for over 63 percent of the credit extended to the private non-financial sector and 75 percent of GDP over the past 25 years. This dependence on bank financing suggests that changes in credit supply, particularly disruptions, can have significant and uneven effects on the real sector.[1] Therefore, understanding the factors that influence credit supply is crucial for policymakers.

However, this task remains challenging due to difficulties in identifying variations in credit supply and their aggregate consequences. The empirical literature has relied on three approaches to tackle this problem. One strand of research uses microdata to examine either the impact of well-identified events or systematic measures of credit supply derived from lending relationships (Khwaja and Mian, 2008; Amiti and Weinstein, 2018). Conversely, some studies focus on bank survey data to understand credit supply shocks stemming from changes in lending standards (Lown and Morgan, 2006; Bassett et al., 2014). Finally, a group of papers adopts a macro perspective and utilizes aggregate data to infer credit supply shocks and their overall effects (Bijsterbosch and Falagiarda, 2015; Gambetti and Musso, 2017; Furlanetto et al., 2019). While this literature has significantly enhanced our understanding of credit supply, these approaches have notable drawbacks. For instance, papers estimating credit supply shocks from microdata on lending relationships can only obtain relative shocks in the cross-section; however, they cannot provide a well-defined measure at the aggregate level. In contrast, papers using survey data face endogeneity issues due to reverse causality between demand and supply. At the same time, those using macro data depend on identifying assumptions that are either too strong or too ad-hoc for the problem.

In this paper, we contribute to the literature by developing an aggregate credit supply indicator that integrates various aspects of the previously mentioned work. Using survey data from the banking sector in Chile regarding changes in lending standards from 2009 to 2023, we create an indicator that takes advantage of the heterogeneity among banks at the credit segment level (i.e., credit to small and large firms, as well as consumer and mortgage credit). We proceed in three steps. First, using the individual responses regarding changes in lending standards and credit demand, we define dummy variables that activate whenever a bank reports tighter lending standards and weaker demand, respectively. This approach preserves the primary information of the survey and enables us to leverage the cross-sectional heterogeneity at both the bank *and* credit segment levels.

[1] See, for example, Peek and Rosengren (2000), Chodorow-Reich (2014), Iyer et al. (2014), Paravisini et al. (2015), Cingano et al. (2016), Acharya et al. (2018) and Jiménez et al. (2020).

Since changes in lending standards often coincide with shifts in credit demand, we take our second step by following Bassett et al. (2014) to address this endogeneity by adjusting changes in lending standards for fluctuations in demand and other unobserved factors. However, unlike Bassett et al. (2014), our methodology leverages heterogeneity at the bank and segment levels, enabling us to control for bank-segment and segment-time fixed effects. By doing so, we account for unobserved confounding variables that capture, among other things, bank specialization and segment-specific shocks, which allows us to obtain changes in lending standards that are orthogonal to these factors.

While this approach provides a better measurement of the credit supply shocks affecting aggregate lending standards, it may still be influenced by common shocks that impact the banking sector and the broader economy, as we do not control for all these forces. Specifically, in addition to idiosyncratic shocks to each bank, some financial factors may impact only the banking system–such as changes in regulation–and aggregate shocks that affect the overall economy. The concept of a credit supply shock should encompass both the idiosyncratic shock and the financial factor but must exclude aggregate shocks.

To make progress in our final step, we make an identifying assumption about the structure of orthogonalized changes in lending standards. We assume they have a factor structure in which the loading on the financial factor is specific to each bank, while the exposure to the aggregate shock is common across all of them. This assumption enables us to differentiate between these two driving forces and simultaneously identify idiosyncratic shocks. With this assumption in place, we utilize the Granular Instrumental Variable (GIV) methodology proposed by Gabaix and Koijen (2024) to account for aggregate shocks. This methodology generates instruments for variables constructed from the aggregation of microeconomic observations that may relate to aggregate shocks by taking the difference between the weighted and unweighted averages of these microeconomic observations. The crucial empirical requirement is the existence of granular units within the economy, ensuring their distribution is not uniform. When this condition is satisfied, GIV can recover aggregate measures free from macroeconomic shocks.

To carry out this final step, we present evidence supporting the existence of granular banks in the Chilean market. We show that credit distribution across banks and segments follows a power law, indicating a fat-tailed distribution. With this evidence, we implement GIV by aggregating the orthogonalized lending standards, weighting them according to each bank's market share within every credit segment, and subtracting the unweighted average. As our identifying assumption

outlines, this difference removes aggregate shocks and accounts for each bank's relative exposure to financial and idiosyncratic shocks. Consequently, our methodology enables us to create a credit supply indicator that reflects aggregate shifts in supply while avoiding any endogeneity concerns.

We further characterize our GIV measure by extending the analysis in three directions. First, we use principal components analysis (PCA) to decompose our aggregate measure based on the relative contributions of idiosyncratic shocks to each bank and shocks common to all (but not to the rest of the economy). This shows that most variation arises from shocks that are common to all banks. Second, we break down our aggregate measure according to the contributions of each credit segment. While credit to households and businesses contributes equally, most of the variation is driven by lending to large firms and mortgage credit. Finally, we utilize our GIV to estimate the slope of sectoral credit demand. By implementing an instrumental variable (IV) strategy, we show that GIV exhibits (i) a positive correlation with interest rates (first-stage regression) and (ii) a negative correlation between credit and instrumented interest rates (IV regression). This evidence indicates that changes in GIV help to identify credit demand and can be interpreted as credit supply shifters.

Equipped with our aggregate banking credit supply indicator, we analyze the aggregate implications of a credit supply disruption in the banking sector. We investigate the response of aggregate credit, economic activity, and prices following a contractionary credit supply shock using a vector autoregression (VAR) methodology while controlling for developments in market finance by incorporating the bond credit spread calculated for Chile (Gilchrist and Zakrajšek, 2012). We execute our VAR with a recursive identification where GIV is ordered first. This identifying assumption is advantageous due to its simplicity and intuitive nature; by definition, GIV is orthogonal to any contemporaneous macroeconomic shock. Our findings reveal that a one standard deviation increase in lending standards decreases credit by 0.5 percent over a two-year horizon, accompanied by a decline in prices and a more accommodating monetary policy.

Additionally, we show that the impact of this shock differs across credit segments, with credit to firms showing a more substantial initial response, whereas credit to households aids in the recovery phase. We conclude by addressing the significance of debt substitution in accurately assessing the aggregate consequences of disruptions in banking credit. We emphasize that determining the responses of these alternative financing sources is essential for accurately measuring the shock's impact as spillovers occur between the markets.

The rest of the paper is organized as follows. Section 2 summarizes the primary dataset of this

paper and our empirical approach. Section 3 presents our main results for the aggregate implications of credit supply disruptions in the banking sector. Finally, Section 4 concludes.

2 Empirical Approach

We create measures of credit supply shocks by utilizing survey data on changes in lending standards from Chilean banks. By integrating this data with banks' balance sheet information, we develop an index representing the likelihood of stringent lending standards, independent of other financial and economic conditions, at the aggregate level. This section outlines our empirical methodology and the data used.

2.1 The Senior Loans Officers' Survey

Bank credit supply encompasses various dimensions related to financial intermediation. These dimensions range from the probability of credit approval–the extensive margin of credit–to the amount of credit extended and the associated terms, such as maturity duration, interest rates, or collateral requirements.

This paper focuses on banks' lending standards and how these standards impact overall credit to households and businesses. Since such standards apply to new loans, our metric reflects changes in the extensive credit margin. We utilize survey data from the Chilean Senior Loan Officers' Survey (SLOS), or "Encuesta de Credito Bancario" in Spanish, to create an index linked to this aspect of credit supply dynamics.

The SLOS is a quarterly survey conducted by the Central Bank of Chile since 2003. It queries senior managers of commercial banks about their perceptions of demand and supply factors influencing credit dynamics. The survey also collects information on changes in lending standards for the primary loan categories and shifts in demand for each category.

Like other surveys, the SLOS requires senior officers to indicate how credit conditions in quarter t have shifted relative to the previous three months for a credit category k. The primary credit categories measured in the Chilean SLOS are (i) commercial credit to large firms, (ii) commercial credit to small firms, (iii) consumer loans, and (iv) residential mortgages for home purchases.[2] Questions about changes in lending standards (supply side) are phrased as follows: *"Over the past*

[2]There are two additional categories related to real estate and construction. Due to data limitations regarding the banks' balance sheet for identifying these types of credit, we do not consider those categories.

three months, how have your bank's credit standards for approving loans of type k changed?" Senior officers must select from five options: (i) strongly loosened, (ii) moderately loosened, (iii) unchanged, (iv) moderately tightened, and (v) strongly tightened. For each period and credit category, the Central Bank generates a credit supply index that reflects the difference between the number of banks reporting that standards are moderately or strongly loosened and those reporting moderate or strong tightening, normalized by the total number of responses.

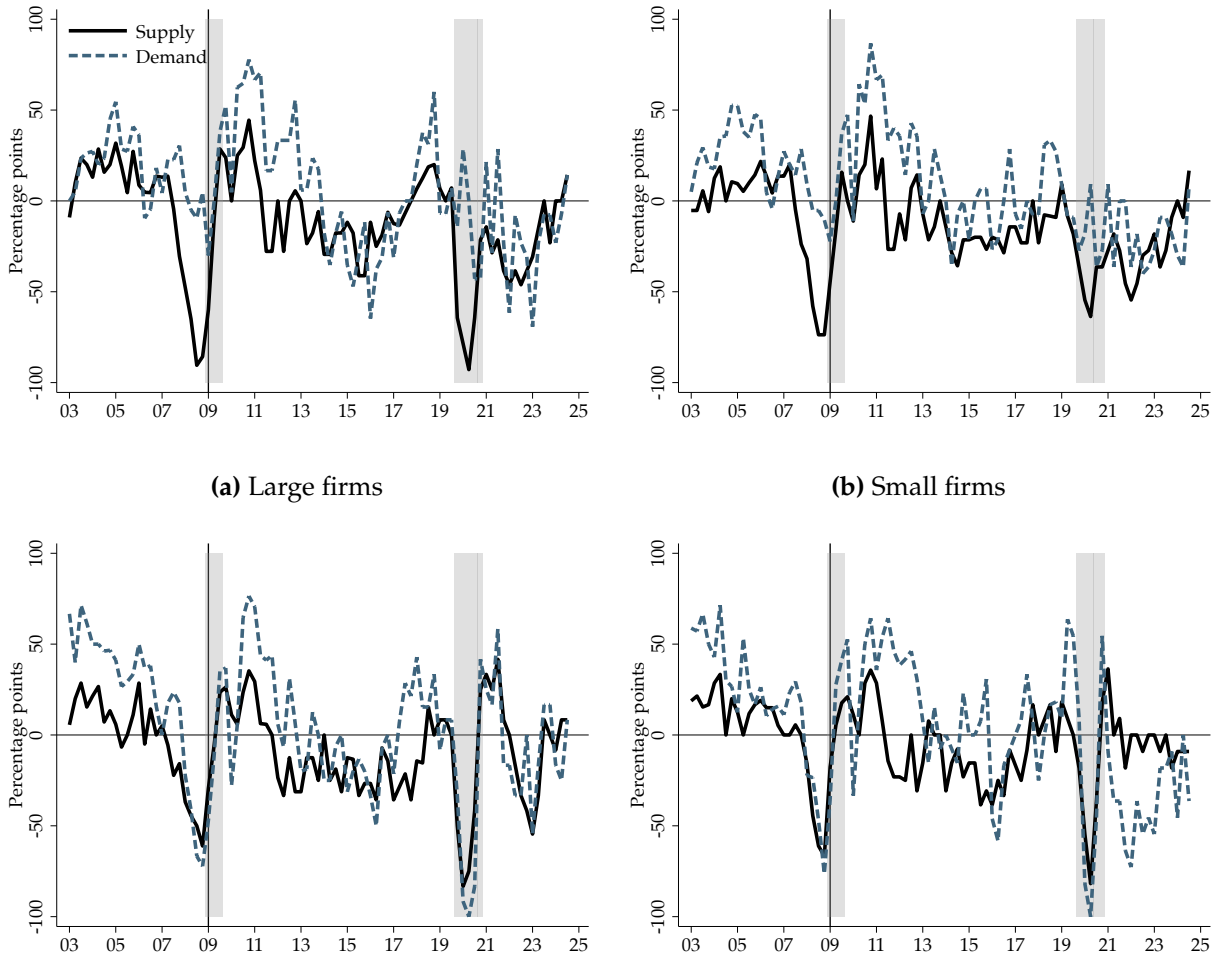
The SLOS also gathers information on the demand side, employing questions that generally take the following form: *"Over the past three months, how has the demand for loans of type k at your bank changed?"*. Similar to the inquiries about lending standards, the possible responses include (i) strongly higher, (ii) moderately higher, (iii) unchanged, (iv) moderately weaker, and (v) strongly weaker. Additionally, like the questions related to supply, an aggregate demand index for each quarter and category reflects the difference between the number of banks reporting strongly or moderately higher demand and those reporting strongly or moderately weaker demand, normalized by the total number of responses.

Fig. 1 presents the evolution of demand and supply indexes for each loan category from 2003 to 2024. There are two observations regarding the figure. First, demand and supply factors are procyclical; the correlation with real GDP growth is 0.39 and 0.54, respectively. Furthermore, lending standards are significantly constrained during recessions. Second, and more importantly, there is a strong co-movement between supply and demand factors across all loan categories, with a correlation exceeding 0.56 overall. As noted by Bassett et al. (2014), this correlation suggests that common disturbances drive supply and demand factors. Therefore, those common factors must be eliminated for SLOS to reflect changes in lending standards effectively.

2.2 Additional Data

We combine the microdata from the SLOS at the bank-credit segment level with three confidential datasets from the Chilean credit registry. First, we utilize balance sheet data at the bank-quarter level. This data provides observable characteristics of banks that may influence the evolution of lending standards. Additionally, this data reports the total amount of credit granted by each institution, distinguishing between credit to firms and households. The latter can be further categorized into consumer credit and mortgage credit. Consequently, the balance sheet data enables us to characterize the portion of total credit from each bank granted to firms and the fraction of credit allocated to households for mortgages and consumer credit.

Figure 1. Time series Evolution of SLOS



(a) Large firms

(b) Small firms

(c) Consumer

(d) Mortgages

Notes: This figure presents the evolution of supply and demand indices for the primary loan categories in the SLOS. All series represent the difference between the number of banks reporting improved conditions and those reporting worse conditions, normalized by the total number of responses. Shaded areas indicate recession periods. Quarterly data covers the period from 2003Q1 to 2024Q3. Source: Central Bank of Chile.

To better characterize the credit provided to firms, we combine this information with a second dataset detailing each firm's credit stock with the banking system. This data enables us to identify borrowers and their sizes, allowing us to differentiate the total credit allocated to firms between credit for large firms and credit for small firms. Following standard practices for constructing national accounts, small firms comprise firms with annual sales below 100,000 UF (*Unidad de Fomento* in Spanish). In contrast, the remaining firms are classified as large.[3] Consequently, these

[3]The UF is the unit of account used in Chile to index payments to monthly inflation, transforming nominal variables

two datasets enable us to characterize the distribution of credit to large and small firms, as well as consumer credit and mortgage credit at the bank-quarter level. These two confidential datasets from the Financial Market Commission (*Comision para el Mercado Financiero* or CMF in Spanish) are available from 2009Q1. As we illustrate below, our methodology heavily relies on the distribution of credit across sectors in banks' balance sheets. Therefore, our analysis is constrained to the 2009Q1-2023Q4 period.

Note, however, that the previous step combines flow data from the balance sheet registry with stock data from the credit stock to firms. We verify the consistency of our results by relying on a third source of data that records all new credit granted to households and firms. We find a similar distribution of credit among different borrower types in the banks' balances. Given that this later data is only available from 2012Q2, we prefer to work with the combined data to maximize the number of time-series observations.

2.3 Constructing Aggregate Changes in Lending Standards

Following the literature, we develop an aggregate credit supply index based on the microdata from the SLOS (Bassett et al., 2014). However, we diverge from earlier studies by leveraging the detailed data available at the credit segment-bank-period level, which enables us to more effectively control for the aggregate and sectoral factors impacting lending standards. The following sections outline a three-step approach to constructing this aggregate index.

Step 1. For each credit segment k, we create the categorical variables I^s_{bkt} and I^d_{bkt}, characterizing the behavior of supply and demand respectively. These indicators are defined as:

$$I^s_{bkt} = \begin{cases} 1 & \text{if bank } b \text{ reports tighter lending standards for segment } k \text{ in quarter } t \\ 0 & \text{otherwise} \end{cases}$$

and

$$I^d_{bkt} = \begin{cases} 1 & \text{if bank } b \text{ reports weaker demand for segment } k \text{ in quarter } t \\ 0 & \text{otherwise} \end{cases}.$$

In constructing these indicators, we defined tighter lending standards whenever a bank reports moderately or strongly tightened standards. Similarly, weaker demand is defined whenever a bank

to real ones. On average, over the 2009Q1-2023Q4 period, one UF corresponds to USD 41.

reports moderately or strongly weaker demand. Consequently, our indicators activate whenever banks perceive a deteriorating credit market scenario (relative to the previous quarter), whether on the demand or supply side. Our approach differs from Bassett et al. (2014), which generates indicator variables based on loose, unchanged, and tight lending standards for each credit segment and then aggregates them at the bank level to produce a diffusion index for each bank period.

Step 2. Even though the supply indicator can provide valuable information about the state of lending standards for a specific bank-credit segment, it can be influenced by the strength of credit demand or factors that affect supply and demand simultaneously. Such comovement creates a bias that distorts our measure of proper changes in lending standards.

To accurately assess how credit standards evolve, we examine the following linear specification

$$I^s_{bkt} = \alpha_{bk} + \alpha_{kt} + \beta I^d_{bkt} + \gamma' \mathbf{X}_{bt-1} + u_{bkt}, \tag{1}$$

where α_{bk} and α_{kt} represent bank-credit segment and credit segment-time fixed effects, respectively, and $\mathbf{X}_{bt-1}$ is a vector of bank-specific controls. The α_{bk} fixed effect accounts for all time-invariant bank-specific factors influencing a credit segment. One interpretation of these factors is the specialization of banks at the sectoral level. Previous literature has demonstrated that bank specialization in lending can lead to significant financial effects related to the allocation of credit, as well as real effects (Chodorow-Reich, 2014; Blickle et al., 2021; Acosta-Henao et al., 2023; Dempsey and Faria E Castro, 2024). Conversely, the fixed effect α_{kt} captures sector-specific shocks that impact credit conditions, such as disruptions in the housing market that affect mortgages. The bank-specific controls included in vector $\mathbf{X}_{bt-1}$ are (i) bank size, measured by the logarithm of assets, (ii) return on assets (ROA), (iii) loan performing ratio, (iv) loan-to-assets ratio, (v) bank deposits ratio, (vi) a capital slackness condition, defined as the gap between effective capital and regulatory capital, and (vii) return on equity (ROE). These variables reflect how changes in banks' performance influence lending standards and are included with one lag to address endogeneity concerns.

The object of interest in Eq. (1) is the residual term $\widehat{u}_{bkt}$. This residual captures changes in lending standards at the bank-segment level, which are orthogonal to demand, bank-specific conditions, and unobserved factors that are heterogeneous across banks, credit segments, and time. For future reference, note that positive values of these residuals indicate tightenings in lending standards that are orthogonal to the factors mentioned above.

Table 1 presents estimates of Eq. (1) for each credit segment, along with pooled estimates.

Columns (1) and (2) show results for the commercial categories of Large Firms and Small Firms, while columns (3) and (4) present results for credit to households (Consumer and Mortgages, respectively). In all credit segments, we observe a positive and significant effect of demand conditions, indicating that weaker demand is associated with a higher probability of tightening lending standards. This result aligns with previous literature and suggests a correlation between demand and supply factors that common shocks may drive.

Regarding bank-specific factors, we report a positive and significant coefficient for bank size, measured as the logarithm of banks' assets. A one percent increase in banks' assets is associated with an increase of more than 6 percent in the probability of tight standards across credit categories, with mortgages being the only segment that is not sensitive to this variable. Regarding other bank-specific covariates, we find little evidence that these variables contribute to the evolution of credit standards, which aligns with previous literature. The exceptions are the loans-to-assets ratio and the bank deposits ratio, which positively impact household standards.

This later conclusion shifts when we examine a pooled estimate in column (5) with clustered standard errors at the bank-segment level. While demand remains positively correlated with lending standards, we find evidence regarding the statistical significance of bank-level controls.

Threats to Identification. Conceptually, changes in the probability of tightening lending standards (orthogonal to demand and unobserved factors) stem from two sources. On the one hand, these changes arise from purely idiosyncratic reasons linked to variations in banks' internal assessments of risk or shifts in business models, among other causes. On the other hand, changes result from developments in regulation and banking supervision or shocks affecting all banks simultaneously. Therefore, the first source of shocks is bank-specific, while the second is common across banks.

Even though in Eq. (1) we strive to capture proper variations in lending standards resulting from these two forces, additional factors that we are not controlling for may distort our residuals. In particular, aggregate shocks affect the macroeconomic environment beyond idiosyncratic shocks or regulatory changes. These aggregate shocks simultaneously influence aggregate demand and supply, contaminating our residuals with a component that falls outside our definition of a credit supply shock and is (incorrectly) interpreted as changes in lending standards. Despite our ability to include observable macroeconomic covariates, further variation could still arise from factors we cannot control. Our final step advances the effort to eliminate sources of variation impacting the macroeconomic environment.

Table 1. Factors Influencing Changes in Bank Lending Standards

	Commercial		Households		Pooled
	Large Firms	Small Firms	Consumer	Mortgages	
	(1)	(2)	(3)	(4)	(5)
Demand	0.10***	0.27***	0.18***	0.13**	0.14***
	(0.02)	(0.05)	(0.06)	(0.05)	(0.02)
Bank size	0.11**	0.07**	0.06***	0.04	0.08**
	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)
Return on assets	6.58	-1.10	13.83	3.66	10.59*
	(6.64)	(6.55)	(9.48)	(10.00)	(5.51)
Loan performing ratio	-0.40	0.74	-0.77	-6.25	-1.62*
	(1.35)	(1.04)	(3.81)	(5.34)	(0.88)
Loan ratio	0.10	0.14	0.23**	0.46	0.34**
	(0.37)	(0.27)	(0.09)	(0.27)	(0.14)
Bank deposit ratio	0.06	0.01	0.56***	0.38*	0.20*
	(0.24)	(0.31)	(0.16)	(0.20)	(0.12)
Capital	-0.00	-0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Return on equity	-1.63	0.18	-0.44	0.16	-1.33*
	(1.55)	(0.99)	(1.21)	(1.00)	(0.75)
R-squared (within)	0.06	0.10	0.07	0.04	0.04
Observations	744	606	628	570	2546

Notes: This table presents estimates of Eq. (1) related to factors influencing changes in lending standards across different credit segments. Columns (1) to (4) include bank and time-fixed effects, while column (5) incorporates bank-segment and segment-time fixed effects. Robust standard errors are clustered at the bank level (columns 1-4) and bank-segment level (column 5), indicated in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Quarterly data covers the period from 2009Q2 to 2023Q4.

Step 3. As previously discussed, our goal is to recover a measure of credit supply shocks that (i) considers the effects of idiosyncratic shocks and common shocks affecting all banks and (ii) is not influenced by aggregate shocks that are common to all agents in the economy. We define

the aggregate shock and the banking shock as η_t and η_t^f, respectively, and we make the following assumption regarding the structure of the error term in Eq. (1):

Assumption 1 *Banks have an idiosyncratic and potentially time-varying exposure to the banking shock η_t^f, but they share a common exposure to the aggregate shock η_t.*

The structure imposed by Assumption 1 indicates that the error term in Eq. (1) can be expressed as $u_{bkt} = \phi_{bt}\eta_t^f + \lambda\eta_t + \varepsilon_{bkt}$, where ϕ_{bt} and λ represent the loadings of the banking and aggregate shocks, respectively, and ε_{bkt} is the actual idiosyncratic supply shock influencing changes in lending standards.

With this assumption in mind, we draw from the Granular Instrumental Variable literature (Gabaix and Koijen, 2024) and construct aggregate changes in lending standards as the difference between the weighted and unweighted (or equally weighted) average of bank-level shocks:

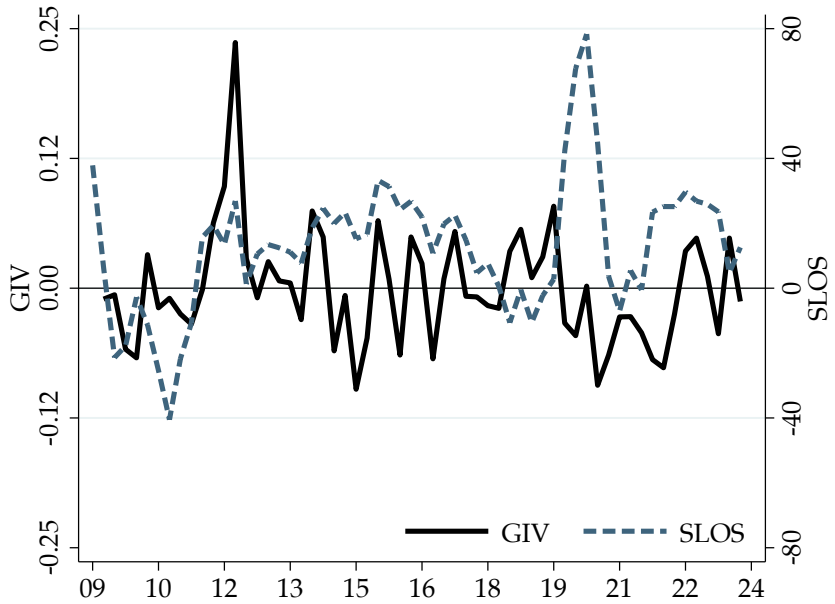
$$\begin{aligned} z_t &= \sum_b \sum_k \omega_{bkt-1} u_{bkt} - \frac{1}{n\kappa} \sum_b \sum_k u_{bkt} \\ &= \sum_b \sum_k \omega_{bkt-1} \Big(\phi_{bt}\eta_t^f + \lambda\eta_t + \varepsilon_{bkt} \Big) - \frac{1}{n\kappa} \sum_b \sum_k \Big(\phi_{bt}\eta_t^f + \lambda\eta_t + \varepsilon_{bkt} \Big) \\ &= \sum_b \sum_k \Big(\omega_{bkt-1} - \frac{1}{n\kappa} \Big) \Big(\phi_{bt}\eta_t^f + \varepsilon_{bkt} \Big), \end{aligned} \tag{2}$$

where ω_{bkt-1} denotes the fraction of aggregate credit in period $t-1$ that comes from bank b in segment k ($\omega_{bkt-1} \equiv L_{bkt-1}/L_{t-1}$, where L represents the amount of credit). We consider the market share from the previous period to avoid reverse causality issues. Finally, n (κ) is the number of banks (credit segments) each quarter. Note that variable z_t in Eq. (2) effectively aggregates the orthogonal changes in lending standards while eliminating aggregate shocks. To see this, recall that aggregate shocks and their loadings remain constant across credit segments and banks, so they cancel out when taking the difference between weighted and unweighted shocks.

Fig. 2 illustrates the evolution of aggregate changes in lending standards from 2009Q1 to 2023Q4. The solid black line, GIV, represents the variable z_t in Eq. (2). With a standard deviation of 0.06, this variable peaks in the first half of 2012, indicating a significant tightening of lending standards. Interestingly, it shows a relaxation of standards at the start of the COVID-19 period. We compare our aggregate measure with the unweighted average of the aggregate supply indexes presented in Fig. 1. We take the negative of this latter variable so that positive values for both measures indicate tighter standards. Both variables exhibit low comovement over time, featuring a correlation of 0.05.

Additionally, unlike variable z_t, the SLOS indicates significant tightening during the pandemic, which persisted throughout by the end of the sample period.

Figure 2. Aggregate Changes in Lending Standards



Notes: This figure illustrates the evolution of aggregate changes in lending standards. The black solid line (GIV) represents the variable z_t in Eq. (2). The blue dashed line (SLOS) represents the negative of the unweighted average of aggregate supply indexes shown in Fig. 1. Quarterly data covers the period from 2009Q1 to 2023Q4.

2.4 Discussion

At this point, it is worth taking stock and highlighting some features associated with variable z_t in Eq. (2). First, the measure accounts for the heterogeneity among banks and credit segments in constructing aggregate changes in lending standards. In particular, variable z_t places more weight on (i) larger banks (higher ω_{bkt-1}), (ii) banks that are more sensitive to common banking shocks (higher ϕ_{bt}), and (iii) bank-credit segments experiencing stronger idiosyncratic shocks (higher ε_{bkt}). This differentiates our measure from previous contributions by allowing us to exploit the differences across credit segments over the cycle. By design, such heterogeneity is not considered in other papers and may be crucial for studying the aggregate implications of changes in lending standards arising from differences over the cycle between credit types.

Second, our aggregation fundamentally depends on the presence of granular banks in the economy, corresponding to large institutions influencing overall lending standards. This is evi-

denced by the significant role of the relative banking size (ω_{bkt-1}) in Eq. (2). To the degree that the bank size distribution is not uniform, our aggregation can capture a sensitive measure of shifts in lending standards. Otherwise, the weighted and unweighted aggregations would offset one another, rendering the aggregate measure equal to zero. In Appendix A.1, we present supporting evidence indicating granular institutions' existence across the bank distribution. Specifically, we demonstrate that the bank-size distribution fits well with a power law, a fat-tailed distribution marked by the presence of granular banks.

Third, even though z_t captures aggregate tightenings in lending standards resulting from banking shocks and idiosyncratic shocks, our construction cannot decompose the relative contribution of each source of variation. However, note that, by Assumption 1, the error term has a factor structure that can be utilized to identify each component. In Appendix A.2, we outline a procedure based on principal-component analysis that allows us to provide such decomposition. Given the granularity of the data and the comprehensive set of fixed effects included in the model, we demonstrate that (i) most of the variation is driven by the banking shock, and (ii) this alternative measure is equivalent to the one presented in Eq. (2).

Fourth, by changing the order in the aggregation in Eq. (2) (first adding across banks and then across credit segments), we can identify the contribution of each credit segment to the overall measure. In Appendix A.3, we present the relative contributions of credit to households (consumer and mortgages) and credit to businesses (small and large firms) to the overall measure, demonstrating that both components are equally important in driving aggregate lending standards. However, when disaggregating these measures, we find that credit to large firms and mortgage credit are the most significant components within each group.

Finally, as our aggregation captures changes in lending standards independent of demand conditions, it can be interpreted as an aggregate credit supply shock. In particular, higher values of z_t are associated with a contraction in overall credit. Using an instrumental variable (IV) strategy and microdata on credit flows across different segments, we run regressions for sectoral credit based on the average interest rate charged to each sector, using z_t as an instrument. If this variable reflects a credit supply shock, our estimates identify the demand curve for sectoral credit. We provide suggestive evidence supporting this interpretation in Appendix A.4. Therefore, from now on, we will refer to z_t as an aggregate credit supply shock.

3 Aggregate Effects of Credit Supply Shocks

This section uses a vector autoregression (VAR) framework to investigate the aggregate implications of tightening lending standards. We describe the data and modeling assumptions and then present our main results.

3.1 Data and VAR Model

Aggregate Data. In addition to our credit supply shock, our baseline VAR model considers the following variables: (i) total bank credit, (ii) real GDP, (iii) the consumer price index (CPI), (iv) the monetary policy rate, and (v) the bond credit spread for Chile, which is constructed following Gilchrist and Zakrajšek (2012). As discussed below, including this variable is critical for adequately quantifying the effects of the shock. This is a standard monetary VAR in the spirit of Bassett et al. (2014). Unlike previous literature, we include credit, GDP, and CPI in logs rather than in differences. This approach is motivated by our interest in the sensitivity of credit and other macroeconomic aggregates rather than in the speed of adjustment of these variables. All data is at a quarterly frequency and is taken from the Central Bank of Chile's database, except for the bond credit spread, which is constructed using data from RiskAmerica. To account for the significant disruption in aggregate GDP observed at the onset of the COVID period, we include a dummy variable for 2020Q2-2020Q3. Subsequently, we will add data to our baseline VAR, which will also come from the Central Bank of Chile.

As discussed above, even though the microdata from the SLOS has been available since 2003, our construction of the credit supply shock relies on portfolio data at the individual bank level, which was not available before 2009. Therefore, our analysis is limited to the period from 2009 to 2023. This constraint motivates us to use a Bayesian VAR (BVAR) with flat priors as our baseline model. For robustness, we also examine the aggregate implications of an increase in lending standards using a simple frequentist structural VAR (SVAR) model, as well as local projections (LP), following Jorda (2005). All specifications include four lags of the endogenous variables, which is the lag length selected by standard information criteria indexes, and we verify that all specifications are stationary.

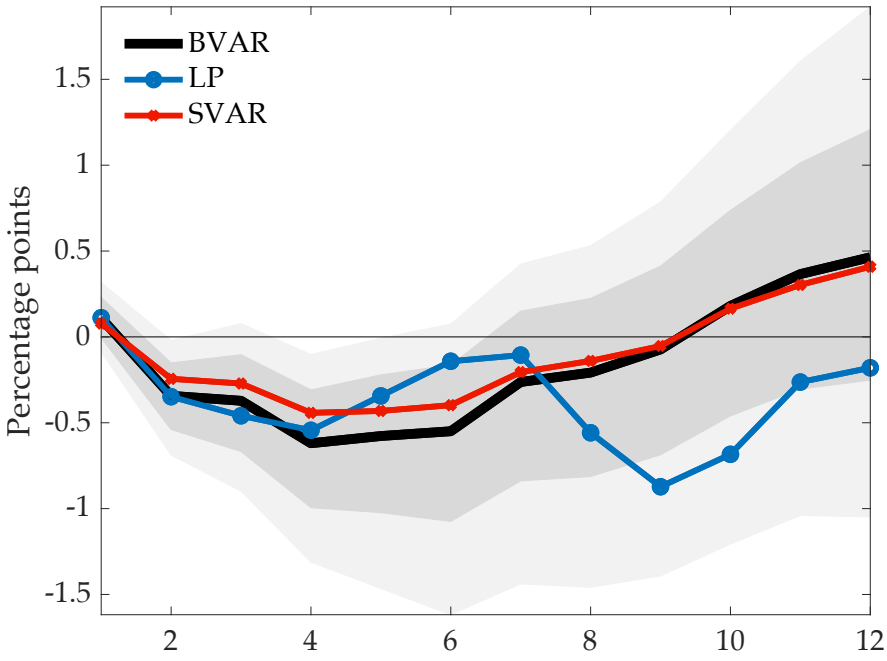
Identifying Assumption. Following Bassett et al. (2014), we utilize a recursive identification in the VAR, with our credit supply shock designated as the first variable. This implies that our shock can immediately affect all aggregate variables while only responding to the economy's subsequent

reactions with a delay. Such an ordering is justified by the construction of our variable, which remains orthogonal to contemporaneous aggregate shocks.

3.2 Baseline Results

Aggregate Responses. Fig. 3 shows the response of aggregate credit (in logs) following a one standard deviation increase in our credit supply variable, which, by definition, indicates a tightening of lending standards and a contractionary credit supply shock. Initially, aggregate credit does not respond to the shock, aligning with the slow-moving nature of debt (Jungherr and Schott, 2022). One quarter after the shock, aggregate credit decreases by 0.4 percent, an effect that persists over the next five quarters, reaching a decline of up to 0.6 percent. After this period, aggregate credit gradually recovers over the next two years. This impact is statistically and economically significant and remains consistent across different estimation techniques, as evidenced by comparing the baseline BVAR results with those obtained from the SVAR and LP models.

Figure 3. Credit response to a Contractionary Credit Supply Shock

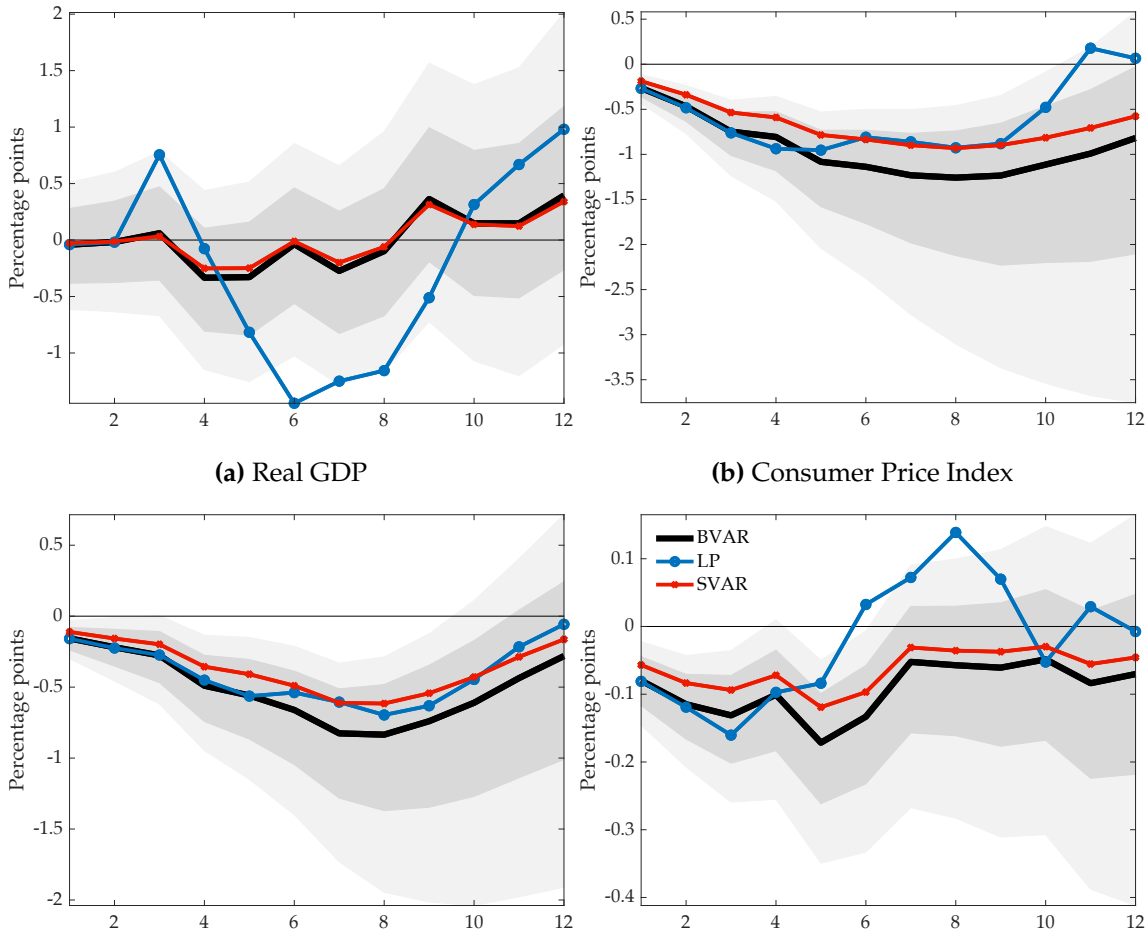


Notes: This figure illustrates the response of aggregate credit following a one-standard-deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows 90 (68)% credible intervals calculated using 10,000 bootstrapped samples.

This shock has implications not only for credit but also for other macroeconomic aggregates. Fig. 4 presents the responses of other variables to the shock. Consistent with previous literature,

real GDP and the CPI negatively respond to the shock, as shown in Fig. 4a and Fig. 4b, indicating a response similar to that observed after a negative aggregate demand shock. Although the output response is not statistically significant, showing a decrease of nearly 0.5 percent one year after the shock, the CPI drops by more than 1 percent in the same timeframe and is statistically significant. In line with the negative responses of output and prices, the monetary policy rate decreases during this period to mitigate the contractionary effects. Conversely, the bond credit spread demonstrates a persistent negative response following the shock.

Figure 4. Aggregate responses to a Contractionary Credit Supply Shock



(a) Real GDP

(b) Consumer Price Index

(c) Monetary Policy Rate

(d) Bond Credit Spread

Notes: This figure illustrates the response of aggregate credit following a one-standard-deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows 90 (68)% credible intervals calculated using 10,000 bootstrapped samples.

The dynamics depicted by Figs. 3 and 4 are consistent with previous literature documenting the

contractionary responses of the economy following a tightening in lending standards. The primary difference lies in the reaction of the bond credit spread, which typically increases after credit supply disruptions in other economies. This outcome aligns with the distinct market structure of corporate debt in Chile compared to other countries, where 94% of bonds are indexed to inflation. Thus, the expansionary response of monetary policy lowers the nominal yield curve, which, combined with a stronger response of the CPI, implies an upward shift in the real yield curve. Since the credit spread represents the difference in yields between corporate and sovereign bonds, most of which are in real terms, this naturally suggests a decrease in these spreads. We test this hypothesis by augmenting the baseline VAR model with 10-year nominal and real sovereign yields, corresponding to the average term to maturity of corporate bonds in Chile (10.82 years). Fig. B.1 illustrates the response of both yields to the credit supply shock, confirming a negative comovement for nominal yields and a positive one for real yields.

The same line of reasoning applies to the results found in the literature. Since corporate debt is primarily issued in nominal terms, the expansionary response of monetary policy suggests that those spreads should rise. However, up to this point, neither previous papers nor our research can conclude that corporate bond yields are increasing after the shock. Below, we explore this issue in greater depth.

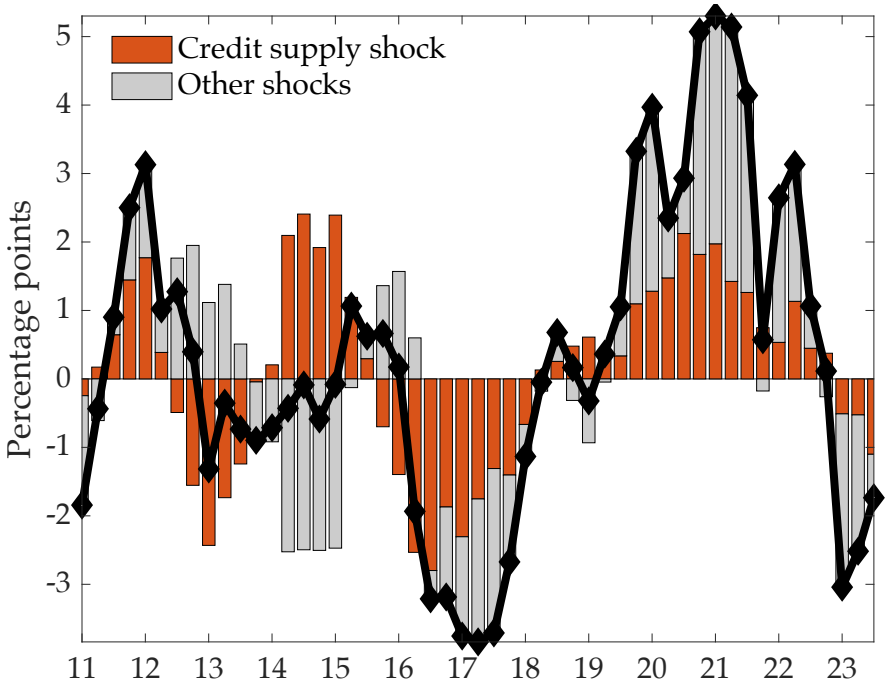
Contribution of Credit Supply Shocks to the Credit Cycle. Next, we examine the significance of credit supply shocks in the evolution of aggregate credit within the economy. To do this, we calculate the historical decomposition of credit and the relative contribution of credit supply shocks compared to other economic drivers.

Fig. 5 illustrates the evolution of credit (in yearly growth rates) and the contribution of each disturbance. In the figure, the black solid line represents the aggregate effect of all shocks in the system, reflecting the evolution of credit in deviations from its deterministic components. As our model can only identify the credit supply shock (shown in red bars), we combine all other shocks into "other shocks" (represented in gray bars).

The figure shows that credit supply shocks have significantly influenced the evolution of credit. Three periods merit particular attention. First, we note a slowdown in credit dynamics followed by a recovery from 2016Q3 to 2018Q3. During this period, credit supply shocks account for about 66 percent of credit growth. This contribution decreases to 42 percent from 2019Q3 to 2022Q3. Interestingly, during this phase, the figure indicates an increase in credit growth with

a positive contribution from credit supply, which contradicts what is observed in the data. This suggests that during the COVID-19 pandemic, other factors help explain the actual decline in credit. We hypothesize that the expansionary nature of our shock is due to credit support policies implemented during those years.[4] Finally, by the end of the sample, the slowdown in credit growth is predominantly explained by other factors, with credit supply shocks accounting for only 37 percent of its evolution.

Figure 5. Historical Decomposition of Credit Growth



Notes: This figure shows the historical decomposition of credit growth derived from the baseline VAR. The horizontal axis represents periods. The solid black line indicates the sum of contributions from each shock in the system.

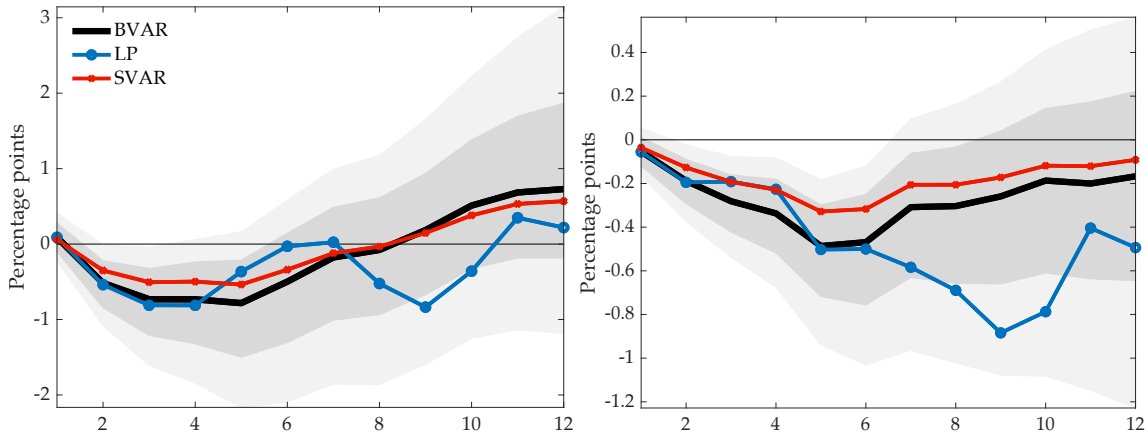
Heterogeneity. Our previous evidence shows that aggregate credit strongly responds to credit supply shocks even after two years. We are now interested in understanding whether such a response is driven by a particular segment of the banking credit market or is a common response across all segments. We extend our baseline specification by splitting aggregate credit into commercial and household credit to address this question. The former represents all the banking credit extended to firms, excluding import and export activities, while the latter includes consumer credit and mortgages.

[4]See Acosta-Henao et al. (2024) for a summary of these policies.

Fig. 6 illustrates the response of both credit segments to the contractionary shock. Similar to aggregate credit, commercial and household credit respond with a one-quarter lag to the shock. Interestingly, these responses are asymmetric. On one hand, commercial credit decreases by up to 1 percent during the first year after the shock and then begins to recover after two years. Conversely, household credit only decreases by up to 0.5 percent over the same period, and the recovery phase is slower. This sluggish response aligns with the idea that households depend more on banks than firms, mainly to finance mortgages, which constitute the bulk of household credit. Conversely, firms have more alternatives for financing, mainly through access to market finance. Simultaneously, both groups can adjust their demand for credit in response to the shock.

This analysis reveals that the depth of the credit response primarily stems from credit to firms, while the duration of the recovery phase is influenced by credit to households. The following sections will explore these results in more detail.

Figure 6. Credit Response to a Contractionary Credit Supply Shock—Heterogeneity



(a) Commercial Credit **(b)** Household Credit

Notes: This figure illustrates the credit response by type following a one-standard-deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows the 90 (68)% credible sets computed with 10,000 bootstrapped samples.

3.3 Understanding the Role of Market Finance

Our earlier discussion emphasized the varied responses of firms and households to the credit supply shock, which are primarily influenced by their unequal access to alternative credit sources. In this section, we explore the role of market finance in propagating bank credit supply shocks.

Theoretical Considerations. While households have fewer alternatives for obtaining consumer credit and mortgages, this is not true for firms. As shown by Adrian et al. (2013) and Becker and Ivashina (2014), firms have access to market finance through bonds, which helps them overcome credit shortages from banks. Moreover, they actively manage their debt structure throughout the business cycle, and substituting among funding sources is especially important for navigating economic downturns and accelerating recoveries (Grjebine et al., 2018). These features have also been studied within theoretical models, reinforcing the results found in the empirical literature (De Fiore and Uhlig, 2011, 2015).

Even though understanding the substitution between sources of finance in the corporate sector is important for assessing the economy's response to contractionary banking supply shocks, there are several caveats to consider. First, this result primarily applies to the United States, where at least 60 percent of firms have access to more than one source of finance (Rauh and Sufi, 2010). Second, there is substantial heterogeneity in market-finance access across firms, which depends on sectoral and firm-specific characteristics (Colla et al., 2013). Finally, even within a sector, this substitutability is concentrated among very large firms, and even among them, the substitution is imperfect and less than one-for-one (Lemmon and Roberts, 2010).

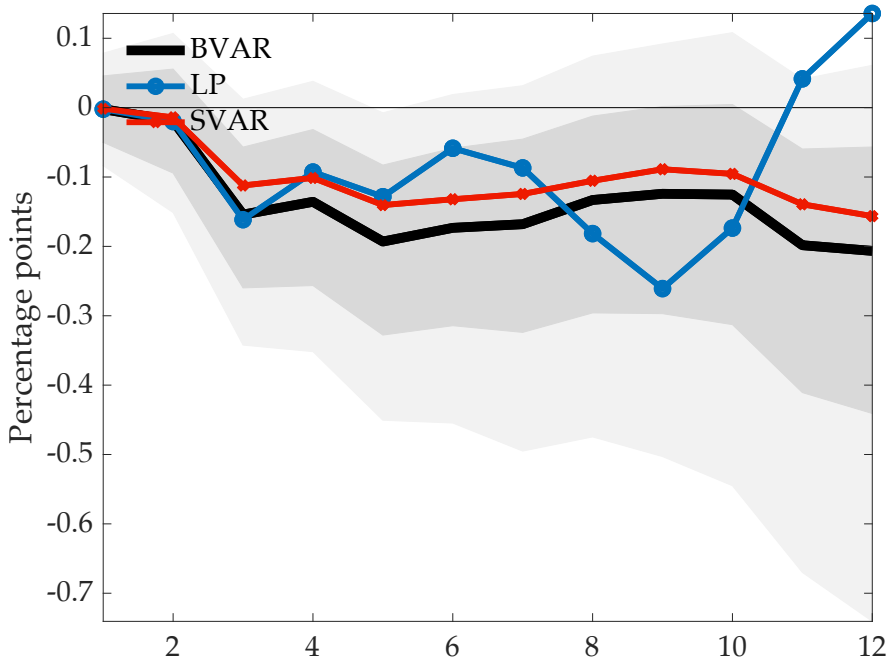
These caveats raise questions about what to expect regarding access to market finance and the response of banking credit following a contractionary shock. Crouzet (2018) studies a model of corporate debt choice and its aggregate implications. In this model, firms sort into two financial regimes: mixed finance (loans and bonds) and market finance (only bonds). The paper shows that the joint determination of investment and debt structure is crucial for generating a complementarity between both sources of debt; the issuance of bonds enables increased investment and larger scale of operations, improving the liquidation value of firms and easing bank borrowing constraints.

After a contractionary bank credit supply shock, two propagation channels emerge. On the one hand, there is the bank lending channel, where firms that depend on bank loans cut back on their borrowing. Simultaneously, firms operating in the mixed regime also reduce their market borrowing due to the complementarity of both debt sources. Furthermore, even though some firms do not rely on bank financing, they still lower their overall borrowing due to precautionary motives, a mechanism highlighted by the empirical literature (Duchin et al., 2010). On the other hand, a debt substitution channel exists, wherein some firms in the mixed-finance regime ex-ante but later only borrowed from markets reduce their total borrowing and scale down operations to mitigate their liquidation risk.

Both channels result in firms reducing their total loans and market borrowing, thereby decreasing leverage. This suggests that failing to account for developments in market finance would produce an upward-biased reduction in banking finance following a contractionary banking supply shock. The deleveraging process in the overall economy would be weaker, indicating a smaller decline in the scale of operations and a lesser decrease in finance needed after the shock.

Evidence for Chile. Although a proper characterization of these mechanisms is beyond the scope of this paper, we provide three pieces of evidence suggesting their validity at aggregate levels. First, we examine the impact of the credit supply shock on the bond market by substituting the bond credit spread with the average yield associated with these instruments. This provides insight into how the shock propagates across markets, a topic not explored yet in the literature. Fig. 7 illustrates a negative response of bond yields to the credit supply shock. This finding indicates that the price of the average corporate bond increases due to the shock, which may result from an expansion in demand or a contraction in supply.

Figure 7. Bond yield Response to a Contractionary Credit Supply Shock



Notes: This figure illustrates the response of the average corporate bond yield following a one standard deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows the 90 (68)% credible intervals calculated using 10,000 bootstrapped samples.

Our second piece of evidence seeks to disentangle which force is behind this response. To this

end, we study the relationship between credit supply shocks and aggregate firm leverage. Fig. 8 plots the correlation between the main components driving aggregate corporate sector leverage and lags of the credit supply shock. The left panel presents the correlation of the shock with bonds and loans, both normalized by assets. The figure reveals that both components decrease after a contraction in banking supply, indicating an aggregate deleveraging process of the corporate sector following the shock. Moreover, the decrease in bond finance is even more pronounced, as shown in the right panel, which plots the correlation of the shock with the share of market finance relative to total debt.

Combining both results, we observe that (i) aggregate leverage decreases and (ii) the rise in corporate bond prices, along with the decline in the bond share as a source of finance, indicates a contraction of corporate bond supply following the shock. What are the implications of our findings? Through the bank lending and the debt substitution channels, the credit supply shock reduces total leverage in the corporate sector, signaling a decrease in production scale, which triggers an amplification mechanism that further diminishes banking credit. Therefore, if we do not account for market conditions, our estimates of the impact of the credit supply shock would be biased upward by neglecting to consider such amplification.

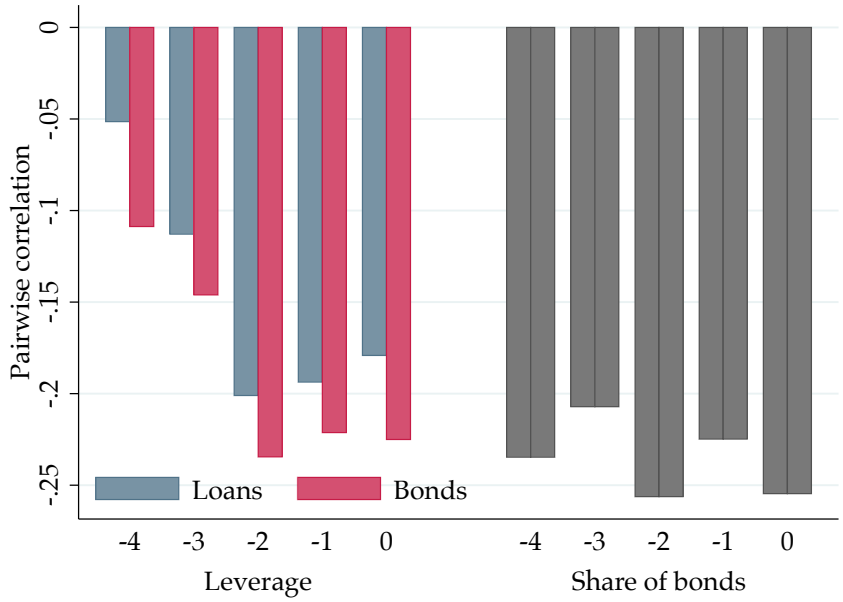
Our final piece of evidence suggests that this is the case. We run our baseline VAR, splitting aggregate credit between credit to firms and credit to households and excluding the bond credit spread or any other measure of market conditions from the estimation. Fig. 9 reveals that the response in credit to households remains unchanged compared to Fig. 6, but the impact on commercial credit disappears. Therefore, it is critical to control for market credit conditions that reflect alternative sources of finance for the corporate sector to correctly measure the impact of banking supply shocks.

3.4 Extensions and Robustness

This section presents extensions and robustness exercises to bolster our baseline results.

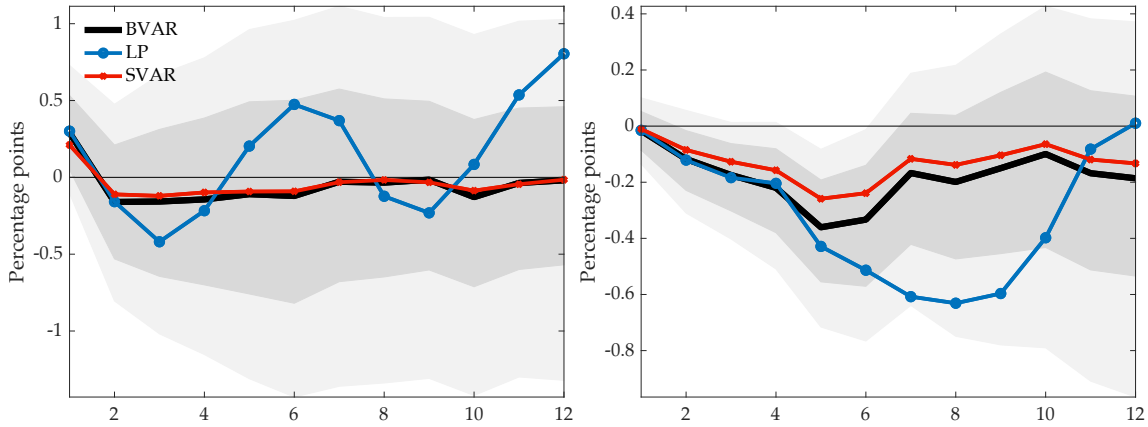
Non-Mining GDP. Chile is an economy characterized by a productive structure concentrated on mining products. On average, mining accounts for 11% of GDP and 15% of total exports. Although Chile is a significant producer of copper and other mining products, the prices of these goods are determined in international markets. Consequently, a considerable portion of aggregate activity is influenced by foreign shocks.

Figure 8. Credit supply Shock and Corporate Debt Structure—Cross-Correlations



Notes: This figure shows pairwise correlations of different lags of the credit supply shock and the corporate debt structure. The left panel displays correlations involving loans and bonds (normalized by assets), while the right panel correlates with the share of bonds relative to total debt. Quarterly data covers the period from 2009Q2 to 2023Q4.

Figure 9. Credit response to a Contractionary Credit Supply Shock—Excluding Bond Credit Spread



(a) Commercial Credit **(b)** Household Credit

Notes: This figure illustrates the credit response by type following a one-standard deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows the 90 (68)% credible sets computed with 10,000 bootstrapped samples.

We analyze how robust the response of aggregate credit is when we consider the evolution of real GDP, excluding mining goods. Fig. B.2 shows credit responses to the credit supply shock when we use this alternative measure. We observe the same patterns as before compared to our baseline result in Fig. 3.

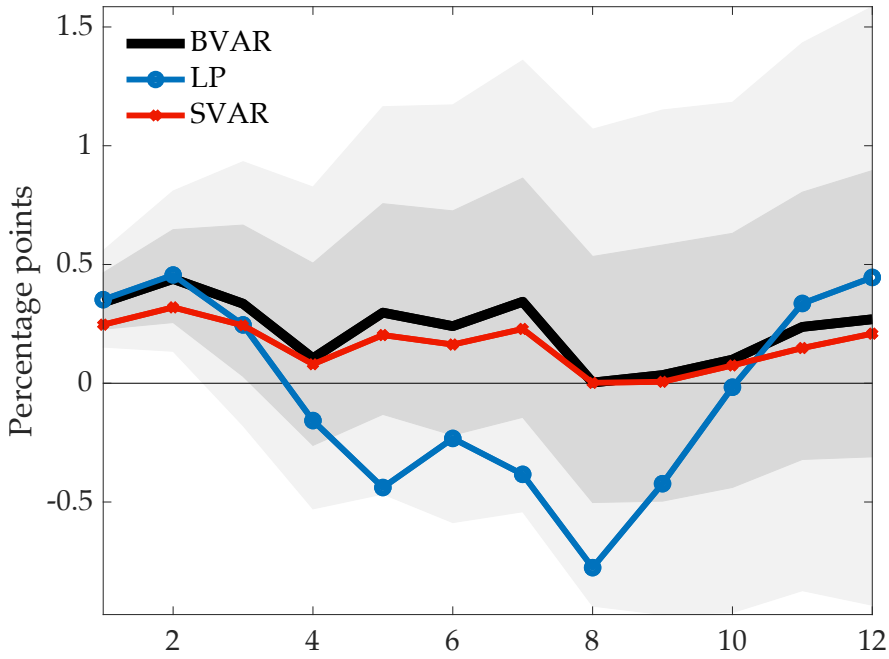
Banking Spreads. In our baseline specification, we analyze the aggregate responses to the credit supply shock, emphasizing the significant decrease in total credit. We enhance this specification by incorporating an aggregate interest rate spread (lending minus deposit rate) to gauge the response of prices and quantities of credit to the shock. Consistent with our previous findings, Fig. B.3 illustrates that aggregate credit declines, accompanied by increased lending margins in the medium term. These results indicate a contraction in the overall supply of credit by banks.

Decomposing the Bond Credit Spread. As pointed out by Gilchrist and Zakrajšek (2012), the bond credit spread can be decomposed into the sum of a factor that prices the probability of default (PD) in the corporate sector and a premium that exceeds this priced risk. This latter factor corresponds to what is known as the Excess Bond Premium (EBP). Are those components relevant for the aggregate responses of credit?

Fig. B.4 illustrates the response of sectoral credit to the shock when using the EBP or the component related to the probability of default as controls. The figure indicates (i) a similar response for credit to households, (ii) a comparable contribution to the decline of commercial credit, and (iii) that both the EBP and the PD decrease with the shock.

Using SLOS. Finally, we examine the implications of credit supply shocks measured directly by combining the raw data in the SLOS. To give this alternative indicator the best chance to generate sensitive responses regarding aggregate credit, we orthogonalize the sectoral supply indicators presented in Fig. 1 by their demand components and aggregate them using a simple average. This indicator removes the demand component at the sectoral level, and we take its negative, so increases in the indicator are associated with tightening lending standards. The credit response to an increase in this measure is shown in Fig. 10 and indicates that using SLOS directly as a credit supply indicator contradicts the notion of a contractionary shock.

Figure 10. Credit Response to an Increase in SLOS



Notes: This figure illustrates the response of aggregate credit following a one standard deviation increase in average SLOS. The horizontal axis represents quarters. The light (dark) gray band indicates 90 (68)% credible sets computed from 10,000 bootstrapped samples.

4 Conclusion

Using data from the Senior Loan Officers' Survey of Chile from 2019 to 2023, we construct an aggregate indicator regarding the banking credit supply stance. To this end, we remove changes in lending standards attributable to demand components and unobservable factors affecting credit supply. Unlike previous literature, we perform this analysis at the bank-credit segment level, allowing us to isolate potential confounders better. We aggregate the residual lending standards by utilizing loan shares at the bank-credit segment level, taking advantage of the granularity of certain banks in the cross-section. Our indicator captures aggregate changes in lending standards that can be interpreted as a contractionary credit supply shock from the banking system, stemming from idiosyncratic forces at the bank-segment level, as well as common shocks to the overall banking system, which we rationalize as common banking shocks and regulatory changes.

Equipped with our credit supply indicator, we show that contractionary shocks can decrease aggregate lending by as much as 0.5% over two years. Furthermore, the shock also reduces prices and the monetary policy rate. We reveal that the impact of the shock stems from the differing

responses in credit to firms and households. While the former drives the intensity of the drop in credit, the latter explains the path of recovery for aggregate lending. Based on this heterogeneity, we provide suggestive evidence indicating that controlling for the overall conditions in other sources of finance for firms, such as the bond market, is essential for accurately quantifying the impact of credit supply disruptions within the banking system. Therefore, our work advises caution regarding the degree of complementarity between different credit sources when analyzing regulation changes within the banking sector.

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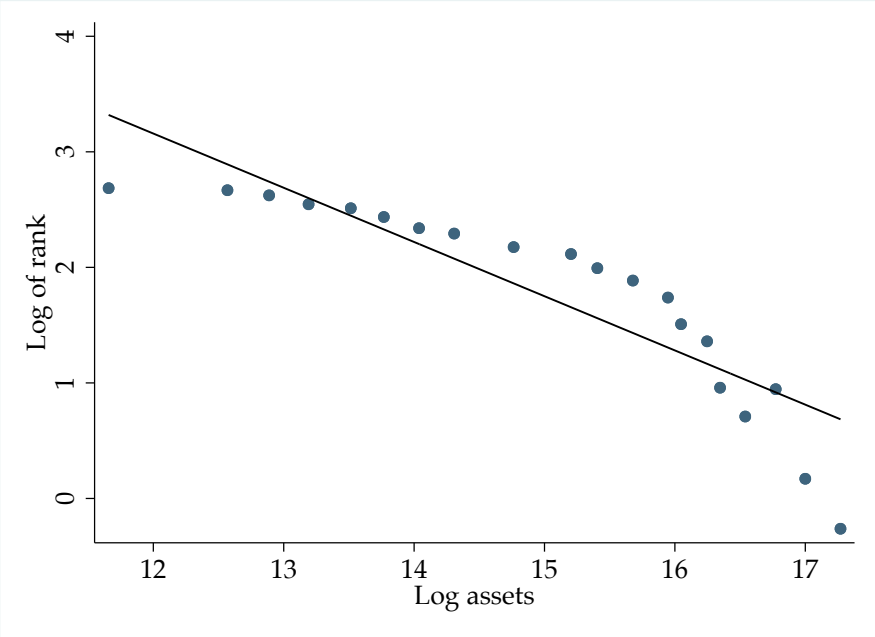
A Additional Results for Lending Standards

A.1 Bank-size Distribution

This appendix offers supporting evidence regarding the presence of granular institutions in the distribution of banks.

Fig. A.1 presents our first piece of evidence by plotting the distribution of banks. By ranking banks' credit in descending order for each period, the figure compares their (log) total credit amount against their (log) rank.[5] The figure suggests a behavior consistent with a power law, where granular units have aggregate implications for total credit.

Figure A.1. Distribution of Ranks and Bank Size



Notes: This figure illustrates the distribution of bank size (log-rank of bank size versus the log of bank size), measured by total credit, along with the linear best fit. The data is plotted net of time-fixed effects and is presented in 20 equidistant bins on the log scale, excluding the lowest 20 percent of observations. Quarterly data covers the period from 2009Q1 to 2023Q4.

We estimate various specifications related to a power law distribution for banks to validate the intuition presented in Fig. A.1. First, we perform a regression of the logarithm of the rank of each bank against the logarithm of its total credit, utilizing the adjustment proposed by Gabaix and

[5] As is standard in the literature (di Giovanni et al., 2011; Bremus et al., 2018), we remove the bottom 20 percent of the data for each period. Our results remain robust to alternative thresholds for this trimming.

Ibragimov (2011), which corresponds to the underlying specification associated with the straight line in Fig. A.1:

$$\ln(Rank_b - 0.5) = \alpha + \zeta \ln(Assets_b) + \varepsilon_b. \tag{A.1}$$

For this regression, we combine data from different periods and include time-fixed effects to account for trends related to the evolution of aggregate credit.

Our second specification directly estimates the slope of the power law. For this, recall that a distributional power law describes a relationship of the form $Pr(X > x) = Cx^{-\zeta}$, where $Pr(X > x)$ is the probability that a random variable X exceeds x, and C and ζ are constants. Based on this definition, we run the following regression:

$$\ln\left(Pr(Credit_b > x)\right) = \ln(C) - \zeta \ln(x) + \varepsilon_b. \tag{A.2}$$

To implement this specification, we create an equidistant grid for values of (log) total credit, which corresponds to the variable x, and estimate the probability $Pr(Credit_b > x)$ as the ratio of the number of banks in the sample with credit larger than x to the total number of banks.

Our final approach utilizes the probability density function (PDF) associated with the power law, which is expressed as:

$$f(x) = C\zeta x^{-(\zeta+1)}. \tag{A.3}$$

To estimate this PDF, we divide the values of banks' credit into bins of equal size on the log scale and compute the frequency as the number of banks in each bin divided by the width of that bin. Since the estimated coefficient represents an estimate of $-(\zeta + 1)$, we report our results by subtracting one from the estimate to recover ζ.

Table A.1 presents the estimates associated with each specification. Across the columns, all estimates are statistically significant, with a standard error implying confidence intervals below one. Moreover, the large R^2 values associated with each specification indicate a good data characterization by a power law. Our results suggest the presence of granular banks in the cross-section.

A.2 A Construction Based on Principal-Components

This appendix illustrates how to decompose the residuals in Eq. (1) into contributions from (i) aggregate shocks, (ii) banking shocks, and (iii) idiosyncratic shocks, following the structure outlined in

Table A.1. Estimates of Power Law Coefficients for Total Credit

	ln(Rank - 0.5)	CDF	PDF
	(1)	(2)	(3)
ζ	-0.47***	-0.21***	-0.63***
	(0.09)	(0.02)	(0.07)
R-squared	0.68	0.88	0.62

Notes: This table presents estimates of power laws related to banks' total credit. Column (1) regresses ln(Rank-0.5) of the bank in the size distribution against the natural logarithm of its size, following Gabaix and Ibragimov (2011), which corresponds to Eq. (A.1). Column (2) estimates the CDF of the power law defined in Eq. (A.2). Column (3) estimates the PDF of the power law outlined in Eq. (A.3). The estimates are calculated while excluding each period's bottom 20 percent of observations. Column (1) includes time fixed effects. Standard errors are clustered at the bank level in column 1 and adjusted for heteroskedasticity in columns 2-3, as indicated in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. Quarterly data covers the period from 2009Q1 to 2023Q4.

Assumption 1, thereby producing an alternative measure of aggregate changes in lending standards. Furthermore, we demonstrate that this alternative measure provides a similar aggregation to what is presented in Section 2.3.

Given the factor structure described by Assumption 1, the first step is to perform a principal component analysis (PCA) on the residuals $\widehat{u}_{bkt}$ in the credit segment dimension, k. This procedure allows us to recover estimates of the time-varying bank-specific loadings ϕ_{bt} that are constant across credit segments. With those estimates in hand, we run cross-sectional regressions (i.e., period by period) of the residuals $\widehat{u}_{bkt}$ on the estimated loadings to recover measures of the aggregate shock and the banking shock. In particular, by running the following specification for each quarter t:

$$\widehat{u}_{bkt} = \alpha_t + \delta_t \widehat{\phi}_{bt} + \varepsilon_{bkt},$$

we can decompose our residuals into (i) the contribution of macroeconomic shocks to lending standards ($\widehat{\alpha}_t = \lambda \eta_t$), (ii) the banking shock ($\widehat{\delta}_t = \eta_t^f$), and (iii) the idiosyncratic shocks (ε_{bkt}).

Finally, we combine residuals across banks and credit segments for each quarter to obtain an aggregate measure of changes in lending standards, adjusted for macroeconomic factors:

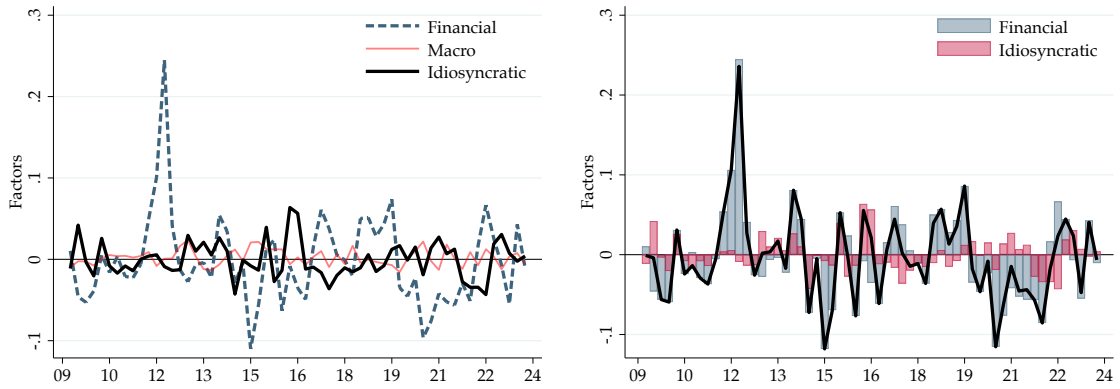
$$\widetilde{z}_t = \sum_b \sum_k \omega_{bkt-1} \widehat{u}_{bkt} = \sum_b \sum_k \omega_{bkt-1} \left(\widehat{\phi}_{bt} \widehat{\eta}_t^f + \widehat{\alpha}_t + \widehat{\varepsilon}_{bkt} \right) = \phi_t^w \widehat{\eta}_t^f + \widehat{\alpha}_t + \varepsilon_t^w, \tag{A.4}$$

where ω_{bkt-1} represents bank b's market share in credit segment k during quarter $t-1$, and $\phi_t^w \equiv \sum_b \sum_k \omega_{bkt-1}\widehat{\phi}_{bt}$ and $\varepsilon_t^w \equiv \sum_b \sum_k \omega_{bkt-1}\varepsilon_{bkt}$ holds. Eq. (A.4) indicates that the aggregate changes in lending standards can be broken down into (i) the average effect of financial shocks, (ii) the overall impact of macroeconomic shocks, and (iii) the average idiosyncratic shock. Utilizing Assumption 1 and the method to identify each factor, the aggregate changes in lending standards excluding macroeconomic shocks are $\widetilde{z}_t - \widehat{\alpha}_t$, which is equivalent to z_t in Eq. (2).

Fig. A.2 shows the results of this alternative procedure. Panel a illustrates the evolution of the components of $\widetilde{z}_t$. Over time, the three factors fluctuate around zero, with the financial factor displaying greater volatility (0.054) compared to the idiosyncratic one (0.022), while the macroeconomic factor exhibits the lowest volatility (0.001). Additionally, the figure highlights the significant spike in the financial factor during the first half of 2012 and its decline in 2015 and throughout the initial year of the COVID-19 pandemic.

On the other hand, panel b illustrates the evolution of aggregate changes in lending standards based on PCA ($\widetilde{z}_t - \widehat{\alpha}_t$), highlighting the contributions of both financial and idiosyncratic factors. The figure shows that the financial factor drives most of the variation.

Figure A.2. Decomposition based on Principal Components



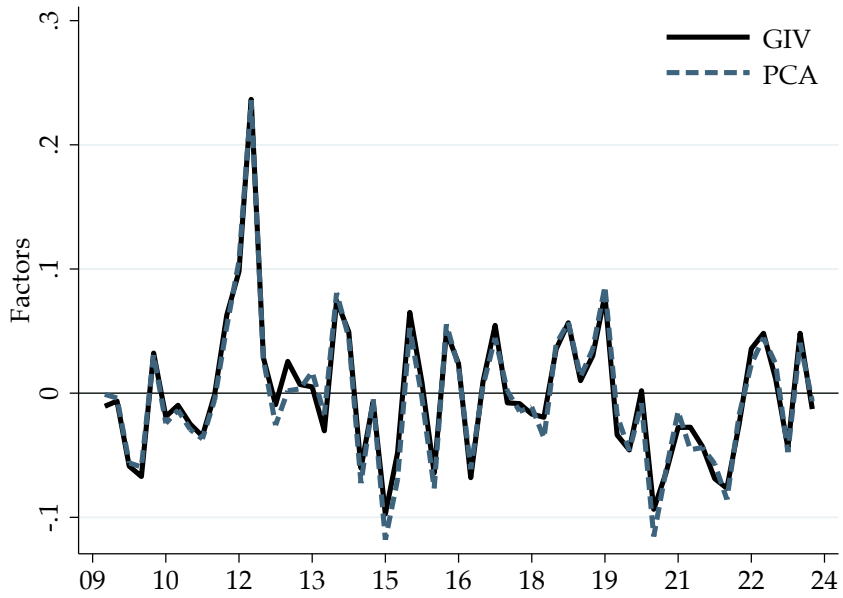
(a) Decomposition of Residuals **(b)** Decomposition of Lending Standards

Notes: This figure illustrates the evolution of aggregate changes in lending standards and its components derived from a principal-components analysis (PCA). The left panel displays the components of aggregate residuals corresponding to Eq. (A.4), labeled as financial, macroeconomic, and idiosyncratic factors. The right panel highlights the aggregate changes in lending standards (PCA), corresponding to the variable $\widetilde{z}_t - \widehat{\alpha}_t$ in Eq. (A.4), and the relative contributions of the financial and idiosyncratic factors. Quarterly data covers the period from 2009Q2 to 2023Q4.

We compare this alternative measure with the one described in the main body of the paper.

Fig. A.3 shows our baseline specification, labeled as GIV, alongside the alternative labeled PCA. As observed in the figure, they are nearly indistinguishable over time.

Figure A.3. Comparison of Aggregate Changes in Lending Standards

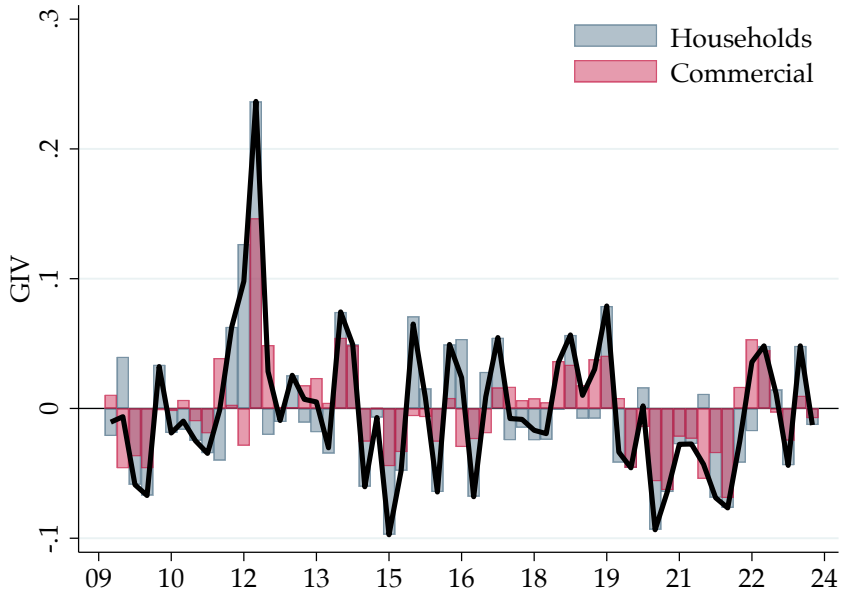


Notes: This figure compares the evolution of aggregate changes in lending standards using different methodologies. The solid black line corresponds to variable z_t in Eq. (2), based on the granular instrumental variable methodology (GIV). The blue dashed line represents variable $\widetilde{z}_t - \widehat{\alpha}_t$ in Eq. (A.4), constructed with principal-components analysis (PCA). Quarterly data covers the period from 2009Q2 to 2023Q4.

A.3 Sectoral Decomposition

As noted in the main text, our measure of aggregate changes in lending standards can be decomposed into the sum of sectoral changes in lending standards. Fig. A.4 presents the evolution of the aggregate measure along with the contributions of credit to households (the sum of changes in lending standards for mortgages and consumer credit) and credit to firms (the sum of changes in lending standards for credit to small and large firms). The correlation between standards for households and firms is 0.2. A variance decomposition of the aggregate measure shows that lending standards for firms contribute 52 percent (18 percent from small firms and 34 percent from large firms), while the remaining 48 percent is driven by standards for households (13 percent from consumer credit and 35 percent from mortgages).

Figure A.4. Sectoral contribution to Overall Changes in Lending Standards



Notes: This figure illustrates the evolution of aggregate changes in lending standards and the relative contribution of each credit segment. The black solid line corresponds to variable z_t in Eq. (2), constructed based on the granular instrumental variable methodology (GIV). The blue bars represent the contribution of credit to households (consumer credit and mortgages), while the red bars depict the contribution of credit to firms (both small and large firms). Quarterly data covers the period from 2009Q2 to 2023Q4.

A.4 Estimating the Sectoral Demand for Credit

To correctly interpret z_t as a credit supply shock, it must be the case that increases in this variable contract the credit supply curve while leaving demand unchanged. Therefore, we can use z_t as an instrument in the following regression:

$$\log L_{bkt} = \beta R_{bkt} + \gamma' \mathbf{X}_{bkt} + \varepsilon_{bkt}, \tag{A.5}$$

where L_{bkt} represents the total credit allocated by bank b to segment k in quarter t, and R_{bkt} and $\mathbf{X}_{bkt}$ indicates the interest rate and other loan characteristics. If z_t acts as a credit supply shock, we anticipate finding (i) a positive correlation with interest rates in the first stage and (ii) a negative correlation between predicted rates and credit (negative β).

To run this regression, we rely on detailed microdata that describe the universe of new loans granted to firms and households. Although this data is more granular, with information at the loan level for each borrower, we aggregate it at the bank-segment level (for firms, mortgages,

and consumer credit) each quarter. This is because utilizing the more granular data accounts for heterogeneity at the borrower level that we cannot control. Furthermore, our goal is to produce an aggregate measure for changes in lending standards, so estimating detailed demand curves is beyond the scope of this paper.

Considering these caveats, Table A.2 presents the results from the first-stage regression of the IV procedure, where we regress the average interest rate at the bank-segment level against GIV while controlling for the average maturity of loans and fixed effects in the banking credit segment (both controls are not reported). Column (1) combines the data, whereas columns (2)-(3) examine the heterogeneity of results across credit segments. Our findings demonstrate a strong and statistically significant relationship between lending standards and interest rates.

Table A.3 presents our estimates of the slope of the demand curve. Column (1) uses the sum of all loans l made by bank b to segment k within a quarter as the dependent variable ($L_{bkt} = \sum_l L_{bklt}$). Panel A displays results for a pooled estimation, while panels B-D show results for each credit segment (all regressions include the average maturity of loans and fixed effects for banking credit segments). From column (1), we observe a negative and statistically significant relationship between predicted interest rates and total credit when examining the pooled data and commercial credit. However, this is not the case for household credit in panels C and D, where the negative coefficient is not statistically significant.

We explore these results further by breaking down total credit into the average amount and the number of credits granted. Denoting n_{bkt} as the number of credits granted and $\overline{L_{bkt}}$ as the average amount, the following relationship holds: $\log L_{bkt} = \log \overline{L_{bkt}} + \log n_{bkt}$. In an abuse of notation but to clarify our point as much as possible, we interpret the average amount as the intensive margin and the number of credits as the extensive margin.

Columns (2) and (3) of Table A.3 utilize these components as dependent variables for the IV regression. In column (2), the average amount is negatively associated with interest rates across all credit segments. Conversely, the number of credits shows no association with interest rates, as demonstrated in column (3). In summary, our measure of aggregate changes in lending standards acts as an aggregate credit supply shock, influencing the intensive credit margin.

Table A.2. First-stage Regression

	Aggregate	Sectoral		
		Commercial	Mortgages	Consumer
	(1)	(2)	(3)	(4)
GIV	9.79***	13.25***	2.07***	12.41***
	(1.63)	(3.54)	(0.20)	(1.64)
R-squared (within)	0.06	0.09	0.07	0.05
F	20.55	12.68	65.13	32.65
Observations	1901	748	545	608

Notes: This table presents the results of the first-stage regression associated with the estimation of Eq. (A.5). The dependent variable is the average interest rate charged by bank b to credit segment k (weighted by loan size) each quarter. Column (1) runs the regression on pooled data and includes bank-segment fixed effects (not reported). Columns (2)-(4) run the regression by credit segment and include bank fixed effects. All regressions control for the weighted average maturity of credits by segment (not reported). Robust standard errors are shown in parentheses and clustered at the bank-segment level in column 1 and at the bank level in columns 2-4. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. Quarterly data covers the period from 2009Q2 to 2023Q4.

Table A.3. Instrumental Variable Regressions

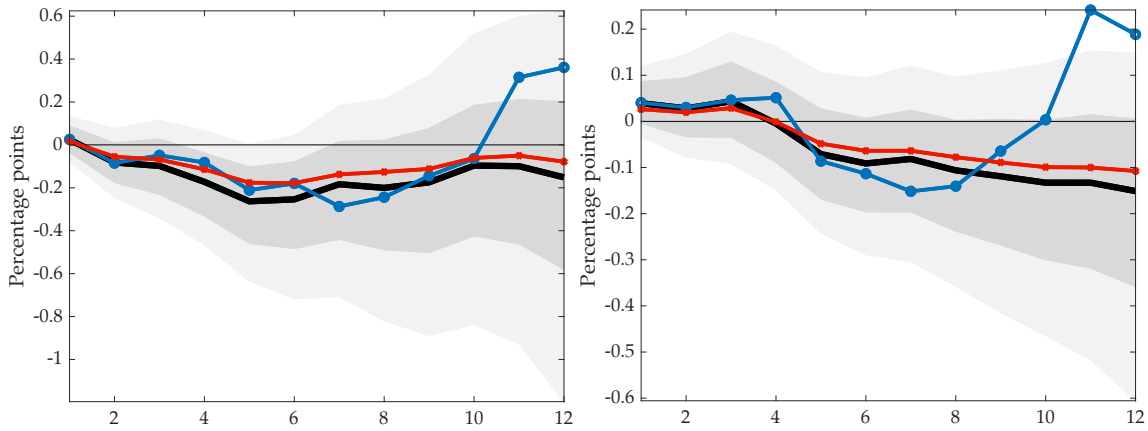
	Dependent Variable			
	Total Credit	Average Amount	# Credit	Observations
	(1)	(2)	(3)	(4)
Panel A: Aggregate Credit				
Rate	-0.09**	-0.13***	0.04	1901
	(0.03)	(0.02)	(0.04)	
Panel B: Commercial Credit				
Rate	-0.11***	-0.16***	0.04	748
	(0.04)	(0.04)	(0.06)	
Panel C: Household Credit–Mortgages				
Rate	-0.36	-0.28**	-0.08	545
	(0.34)	(0.11)	(0.38)	
Panel D: Household Credit–Consumer				
Rate	-0.01	-0.07***	0.06*	608
	(0.04)	(0.02)	(0.03)	

Notes: This table presents the results of the instrumental variable regression associated with the estimation of Eq. (A.5). The dependent variable in columns (1)–(3) is expressed in logs and corresponds to the total amount of credit, the average amount of credit, and the number of credits granted by bank b to credit segment k in each quarter, respectively. Panel A conducts the regression on pooled data and includes bank-segment fixed effects (not reported). Panels (B)-(D) conduct the regression by credit segment and include bank fixed effects. All regressions control for the weighted-average maturity of credits by segment (not reported). Robust standard errors are clustered at the bank-segment level (Panel A) and bank level (Panels B-D), presented in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. Quarterly data covers the period from 2009Q2 to 2023Q4.

B Additional Results for VAR Analysis

B.1 The Response of the Nominal and Real Yield Curves

Figure B.1. Response of Nominal and Real Yields to a Contractionary Credit Supply Shock

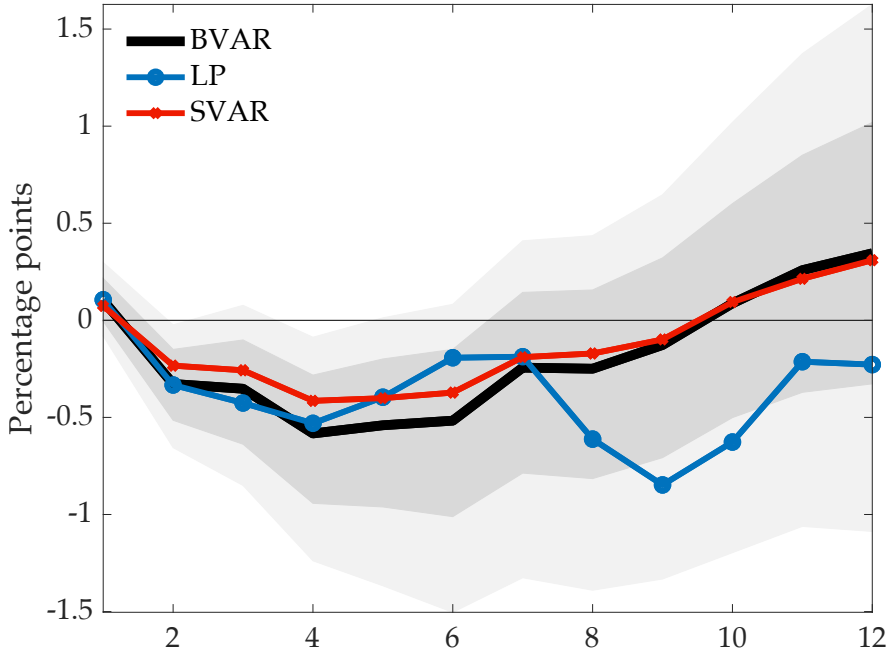


(a) Nominal 10-year Yields **(b)** Real 10-year Yields

Notes: This figure illustrates the response of sovereign nominal and real yields following a one-standard deviation increase in the credit supply variable. The left panel shows the response of nominal yields, while the right panel displays the response of real yields. The horizontal axis represents quarters. The light (dark) gray band indicates 90 (68)% credible sets calculated using 10,000 bootstrapped samples.

B.2 Controlling for Non Mining GDP

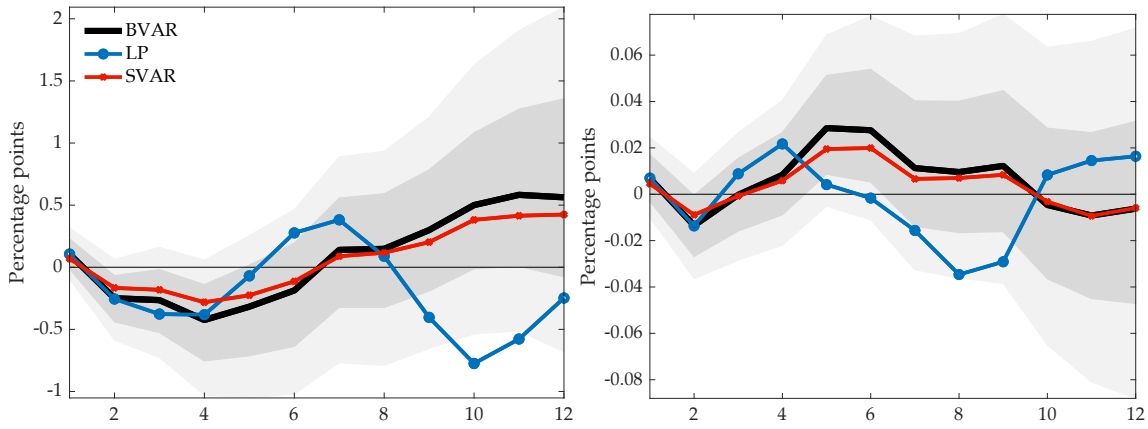
Figure B.2. Credit Response to an Adverse Credit Supply Shock—Controlling for Non-Mining GDP



Notes: This figure illustrates the response of aggregate credit following a one-standard deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band shows 90 (68)% credible sets calculated with 10,000 bootstrapped samples.

B.3 Credit and Banks' Interest Rates

Figure B.3. Credit and Interest Rate Spread Responses to an Adverse Credit Supply Shock

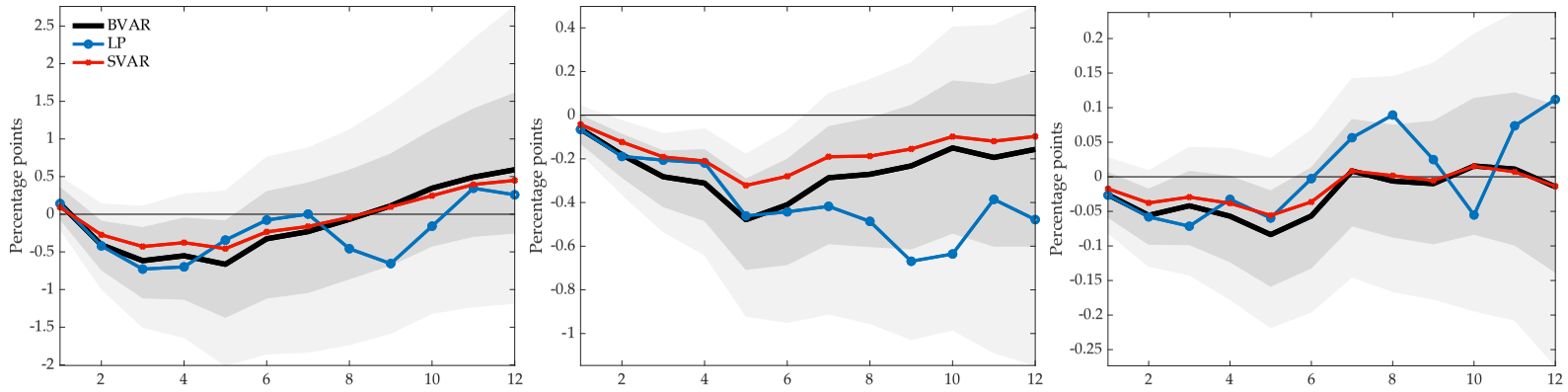


(a) Aggregate Credit **(b)** Interest Rate Spread

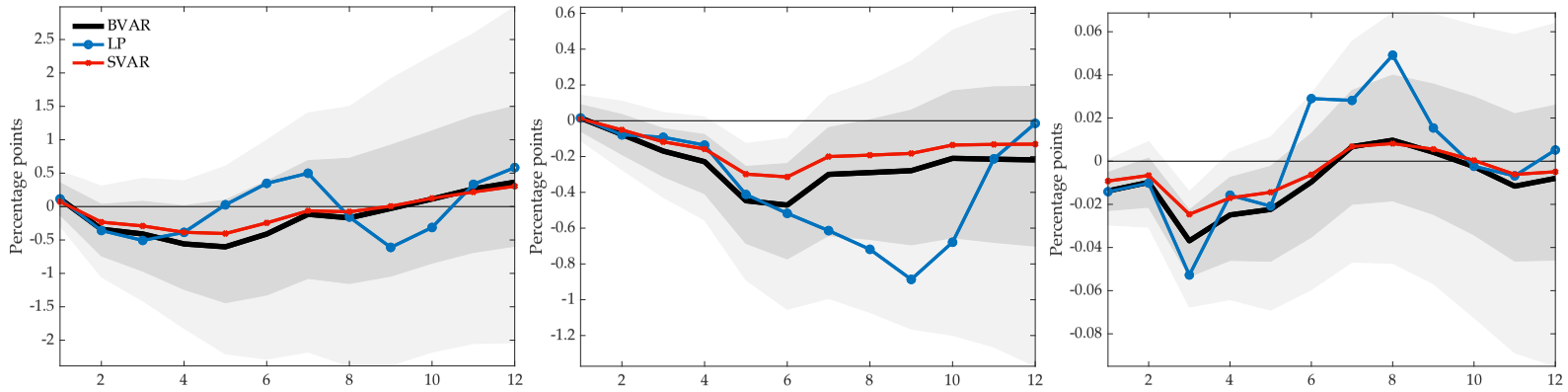
Notes: This figure shows the credit response by type following a one-standard deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray band indicates 90 (68)% credible sets calculated with 10,000 bootstrapped samples.

B.4 Decomposing the Bond Credit Spread

Figure B.4. Credit Response to a Contractionary Credit Supply Shock—Decomposing Bond Credit Spread



(a) Commercial Credit **(b)** Household Credit **(c)** Excess Bond Premium



(d) Commercial Credit **(e)** Household Credit **(f)** Probability of Default

Notes: This figure illustrates the credit response by type and the components of the bond credit spread following a one standard deviation increase in the credit supply variable. The horizontal axis represents quarters. The light (dark) gray bands show 90 (68)% credible sets calculated using 10,000 bootstrapped samples.